Topic Modeling as an Analysis Tool to Understand the Impact of the Iraq War on the Iraqi Blogosphere

by

Mossaab Bagdouri

State Engineer, ENSIAS, Morocco, 2007

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____

Leysia Palen (chair)

____

Kenneth Anderson

____

Gloria Mark

____

James Martin

Date ______________________

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Topic Modeling as an Analysis Tool to Understand the Impact of the Iraq War on the Iraqi Blogosphere

Thesis directed by Professor Leysia Palen

Social media provide a democratized platform for expressing one’s opinion or viewpoint. The everyday discussions that people have with their families, friends and colleagues became available through blogging services. The emergence of the blogging activity made the classic ethnographic approaches more difficult to deploy. The use of these methods becomes even more problematic when the available data contain a wide variety of languages. This thesis proposes the use of topic modeling as a method for quantitatively analyzing crawled blogs that were created by Iraqi citizens and active over a period of 8 years since the beginning of the Iraq war in 2003. This document presents how data were collected, the way dominant languages were separated in different datasets, the limits of using classification and clustering techniques, the benefits of employing topic modeling, and the evaluation of this technique.

Dedication

To mom and dad,

Khadija, Chahid and Jannat,

Amine, Abderrahman and Hiba.

Acknowledgements

I would like to express my sincere gratitude to my thesis advisor Dr. Leysia Palen for her academic guidance and personal support; and my graduate advisor Dr. James Martin for introducing me to the Natural Language Processing world and providing the motivation I needed for this project.

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Chapter 1 Introduction

1.1. Iraqi War and Social Media

It took less than 4 decades to transform the 1960's ARPANET military project to the widely used platform for research, education, entertainment and social communication that the Internet is today. This rapid emergence of Internet access and services provided, however, was not experienced uniformly around the world. The progress of the Internet in Iraq was interrupted by 2 wars, an embargo and state censorship. The Regional Documentation Center, hosted in Al-Mustansiriyah University in Baghdad, had about 1000 dial-up users in 1989, and benefited from connections to Western database vendors [4]. These connections were cut the day Iraq invaded Kuwait on August 2, 1990 [7][8]. In 1998, the government established The General Company of Internet and Information Services, which allowed Internet access to Iraqi citizens 2 years later [2]. State monitoring didn't encourage Internet expansion, and by 2002, there were only 45,000 Internet users within a population of 24 million people [2]. The US invasion in 2003 “destroyed what remained of Iraq’s brittle infrastructure” [3]. But a few months later, engineers from the

State Company for Internet Services succeeded in establishing an Internet café with a satellite transceiver, 50 computers and a diesel generator [4]. There were 150 Internet cafés in Baghdad in 2004, and 2000 nationwide in 2007 [4]. In 2008, about 1% of the population had Internet access. Even if this value represents an important increase in Internet availability compared to previous years, the accessibility remains very low compared to the region and in the world (Figure 1).

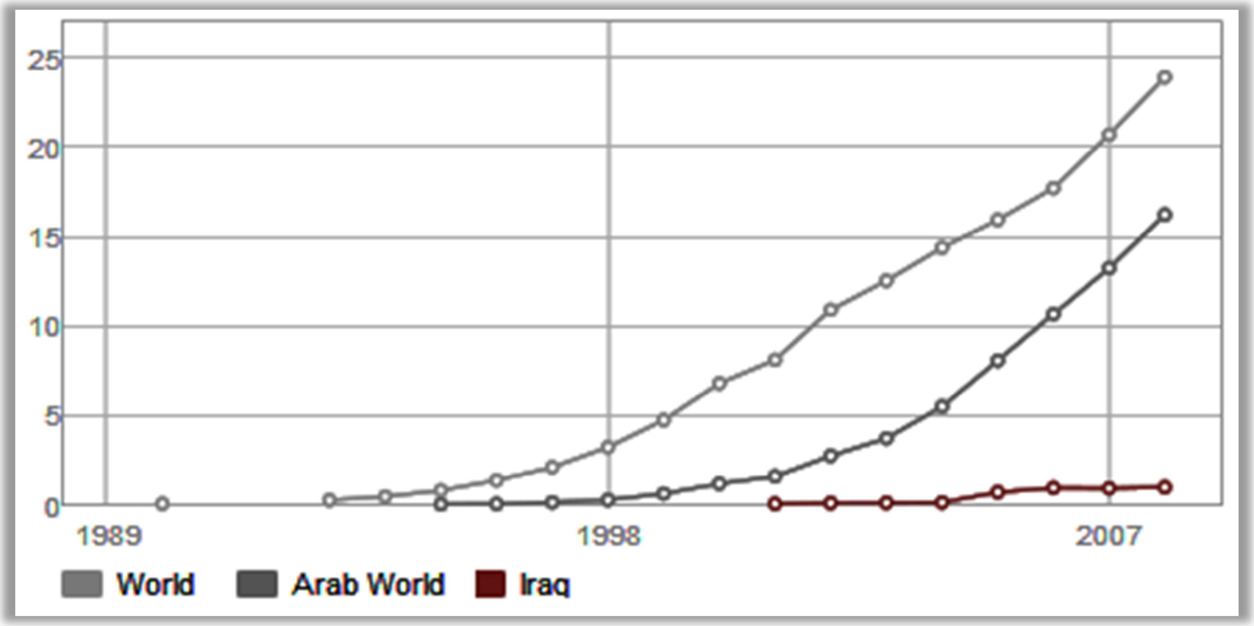


Figure 1: Growth of Internet users as a percentage of population[1]

“Why have persians taken to blogging so easily than arabs? why isn't there a single arabic weblog?” This post published in December 2002 was one of the earliest posts that marked the birth of the Iraqi blogosphere. The author, Salam Pax, is known for being the first Iraqi blogger [15]. In his blog *Where is Raed?*[2] and later *Shut up you fat* whiner,[3] he started to report and

[1] The World Bank: http://data.worldbank.org/indicator/IT.NET.USER.P2/countries/IQ-1A-1W?display=graph

[2] http://dear_raed.blogspot.com

comment on various topics such as Saddam's regime, finance, the Iraqi war, but also daily life and Internet accessibility challenges. Other Iraqi citizens have begun blogging since that time within Iraq and abroad. They expanded the coverage of topics to other interests including but not limited to art, culture and religion.

1.2. Thesis Background and Contribution

While information was for a long time monopolized by official sources and traditional media, the emergence of blogs and social media platforms provided a rich source of information that represent an interesting addition, if not an alternative to the existing ones. Project EPIC (Empowering the Public with Information in Crisis)[4] is a "research effort to support the information needs by members of the public during times of mass emergency." This research covers a wide range of disciplines from human behavior studies to policy issues to microblogging during natural hazards and blogging during times of political conflict.

As part of the EPIC project, the work behind this thesis focuses on the use of blogs during the Iraqi war by Iraqi citizens. In this dissertation, I start in chapter 2 by presenting my method for gathering and preprocessing the blogs. Then I discuss, in chapter 3, the challenges limiting the analysis of this data by some classical NLP approaches. Chapter 4 is dedicated to the choice of topic models as a promising alternative. In chapter 5 I evaluate the output of topic modeling with an external measure. I conclude in chapter 6 and provide an overview of future work.

[3] http://justzipit.blogspot.com

[4] http://epic.cs.colorado.edu

Chapter 2 Data Gathering

Collecting enough data is a first order step to allow quantitative analysis of any phenomenon. In this chapter I introduce the Blogger platform. I then present the crawling of blogs based on Blogger API. I describe the size of the dataset before discussing its preprocessing.

2.1. Blogger

Blogger is a blog-publishing platform that allows users to create blogs, publish posts and interact by comments. A blog is generally hosted at [subdomain].blogspot.com, and can be set to have public or private access. Figure 2 captures the main elements that compose the structure of Blogger service. A profile is a user account and can have multiple blogs. Each blog can have multiple posts. Each post can have multiple comments. A comment can be anonymous, that is its author is unknown, or owned by a profile, i.e. related to a blogger user account.

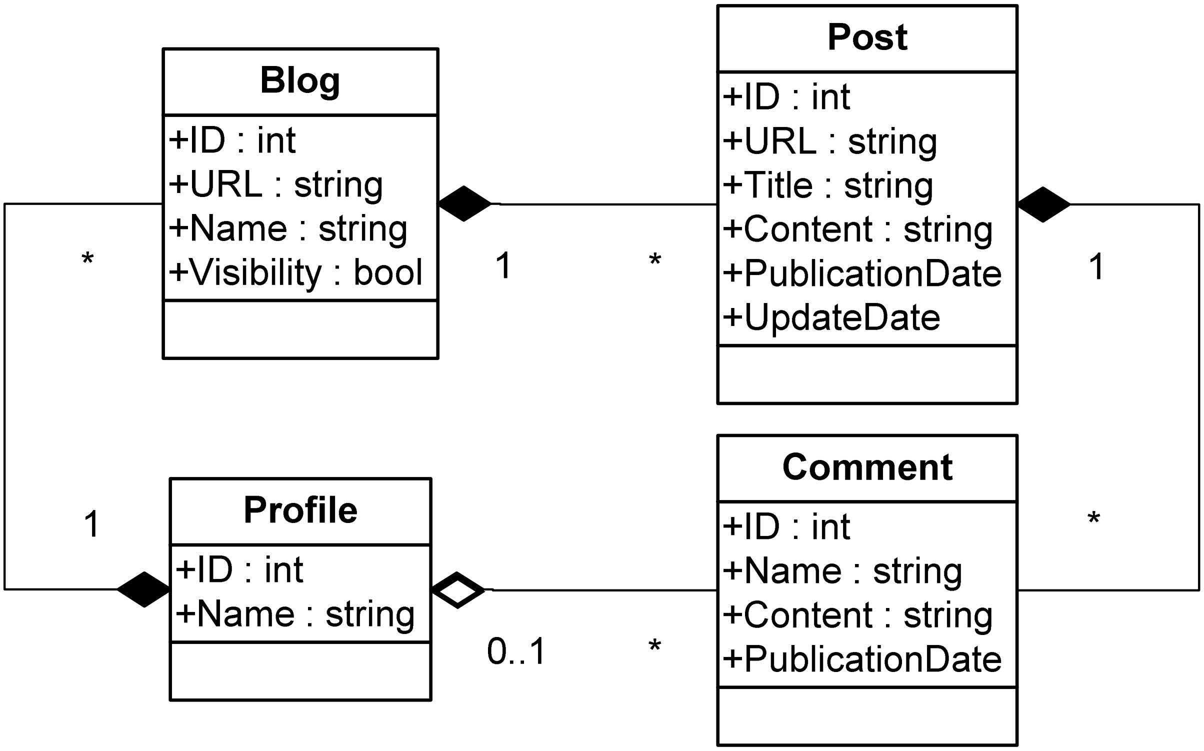
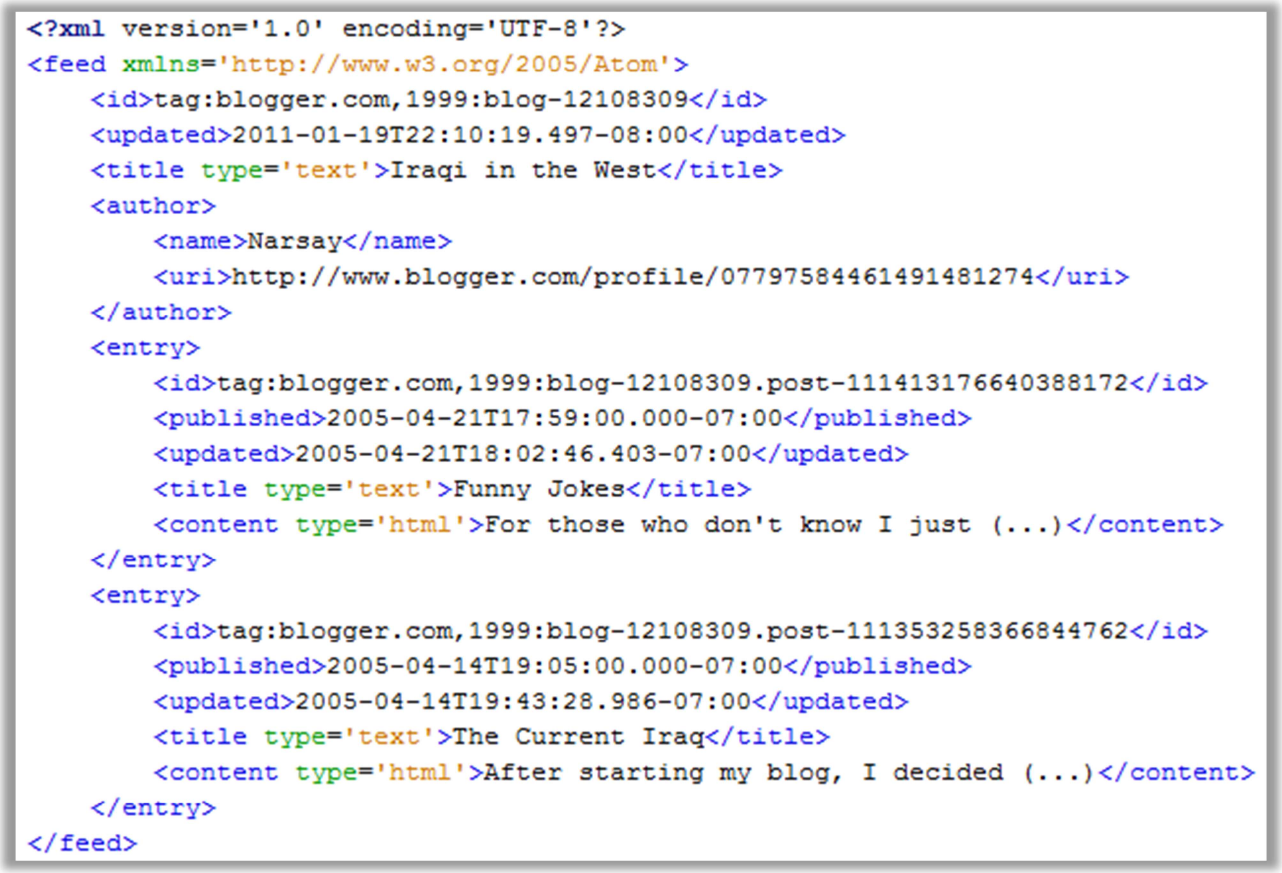


Figure 2: Simplified Class Diagram of the Blogger Service

2.1.Blogger API

Blogger API is a framework that allows developers to access and edit blog contents through an ATOM feed based on Google Data API. The interaction between a client application and Blogger API can be performed via the HTTP requests GET, POST, PUT, and DELETE. As in this research I am interested in retrieving contents from Iraqi blogs, I will need to use only the request GET. Figure 3 illustrates an excerpt of the returned response of the request ***GET /feeds/12108309/posts/default***. This is a call to get the posts of the blog of id 12108309. The response contains informations about the blog such as its title and owner (author). The response provides also a list of posts. A post is presented as an "entry" with an id, publication and update date, title and content (I didn't show all of the content because of space limitations).



```
<?xml version='1.0' encoding='UTF-8'?>
<feed xmlns='http://www.w3.org/2005/Atom'>
    <id>tag:blogger.com,1999:blog-12108309</id>
    <updated>2011-01-19T22:10:19.497-08:00</updated>
    <title type='text'>Iraqi in the West</title>
    <author>
        <name>Narsay</name>
        <uri>http://www.blogger.com/profile/07797584461491481274</uri>
    </author>
    <entry>
        <id>tag:blogger.com,1999:blog-12108309.post-111413176640388172</id>
        <published>2005-04-21T17:59:00.000-07:00</published>
        <updated>2005-04-21T18:02:46.403-07:00</updated>
        <title type='text'>Funny Jokes</title>
        <content type='html'>For those who don't know I just (...)</content>
    </entry>
    <entry>
        <id>tag:blogger.com,1999:blog-12108309.post-111353258366844762</id>
        <published>2005-04-14T19:05:00.000-07:00</published>
        <updated>2005-04-14T19:43:28.986-07:00</updated>
        <title type='text'>The Current Iraq</title>
        <content type='html'>After starting my blog, I decided (...)</content>
    </entry>
</feed>
```

Figure 3: Example of Blogger Feed

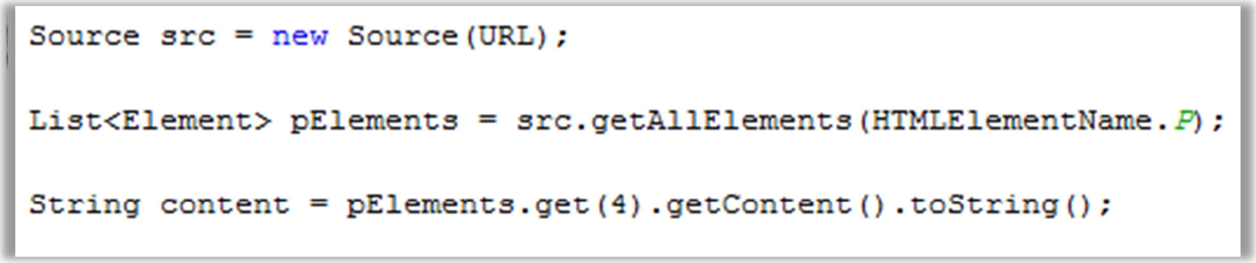
The requests used in the crawler were

- **Profile request**: Retrieval of author information and the list of blogs owned by a given profile (GET /feeds/[profile-id]/blogs).
- **Blog request**: Retrieval of blog information and the list of posts for a given blog (GET /feeds/[blog-id]/posts/default).
- **Post request**: Retrieval of post information and the list of comments for a given post (GET /feeds/[blog-id]/[post-id]/comments/default).

In many cases, the owner of a blog may want to increase the traffic to his blog. He can, thus, set the blog feed to show only a summary of the post entry instead of the whole content. In this case, the Blogger API will not be sufficient for getting a post's full content, and I will have to get this content directly from the post's page.

2.2. Jericho

Jericho HTML parser[5] is an open source java library that enables the parsing of HTML documents. One of the main reasons for choosing this API is its simplicity. Figure 4 shows a piece of code to get the content of the 5th <P> tag from a page hosted at [URL].

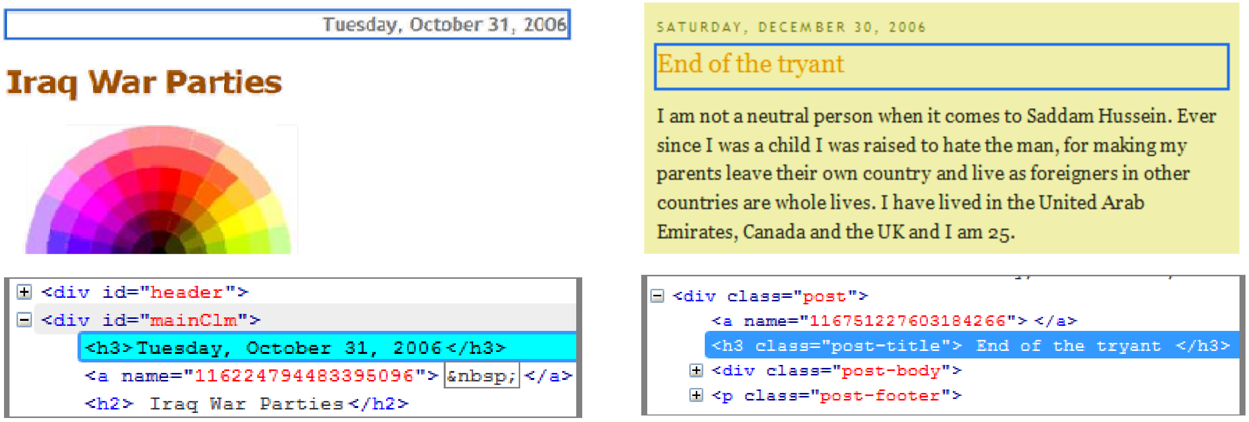


```
Source src = new Source(URL);

List<Element> pElements = src.getAllElements(HTMLElementName.P);

String content = pElements.get(4).getContent().toString();
```

Figure 4: Code Sample for Extracting the Content of a Tag from an HTML Page

The main challenge, though, was that the design differs widely from one blog to another. Figure 5 shows different uses of the HTML tag <H3>. In (a) it is used to format the date, while it is used in (b) to show the title. I found a solution to this problem by accessing the page that allows emailing, to a friend, the link to a post. This page, unlike the original post page, is style independent, and can be easily parsed by my crawler.

[5] http://jericho.htmlparser.net



Tuesday, October 31, 2006

Iraq War Parties

```
⊞ <div id="header">
⊟ <div id="mainClm">
      <h3>Tuesday, October 31, 2006</h3>
      <a name="116224794483395096">&nbsp;</a>
      <h2> Iraq War Parties</h2>
```

SATURDAY, DECEMBER 30, 2006

End of the tryant

I am not a neutral person when it comes to Saddam Hussein. Ever since I was a child I was raised to hate the man, for making my parents leave their own country and live as foreigners in other countries are whole lives. I have lived in the United Arab Emirates, Canada and the UK and I am 25.

```
⊟ <div class="post">
     <a name="116751227603184266"> </a>
     <h3 class="post-title"> End of the tryant </h3>
   ⊞ <div class="post-body">
   ⊞ <p class="post-footer">
```

Figure 5 (a, b): Style Differences Between Two Blogs[6, 7]

2.3. Crawling

I developed an application to crawl a list of Iraqi blogs indexed at iraqblogcount.blogspot.com and iraqiblogindex.blogspot.com to create the dataset. I chose to limit this crawler to the blogs hosted on blogspot.com because of the comprehensiveness and access to the Blogger API 2.0 (as described in section 2.1). These 2 indices contained 366 blogs; however 94 of them were not publicly available. While trying to access them, blogspot.com returns an error message stating that a blog either does not exist, or is not publicly available. A non-existent blog can be the result of either an indexation error from the original 2 indices, a removal by its author or a violation of terms of service[8]. An author can also restrict the access to his blog to a predefined list of readers. I captured the remaining 272 in their entirety. Since many authors write multiple blogs, a scan of the 272 publicly available blogs led to the discovery of 185 additional blogs written by the same authors. I captured these blogs as well, leading to a final data set of 457 blogs containing 46,828 individual posts and 188,011 comments covering

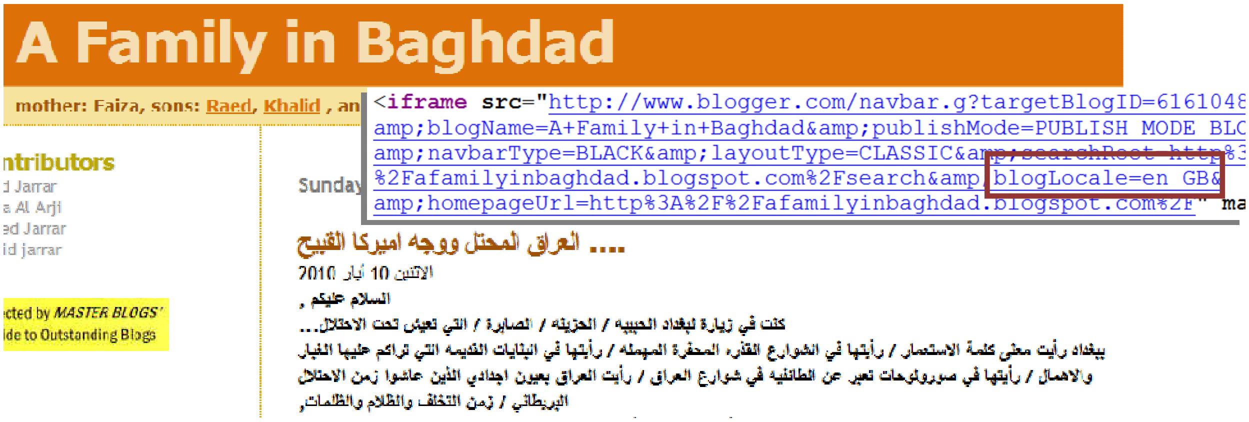
[6] http://glimpseofiraq.blogspot.com/2006/10/iraq-war-parties.html

[7] http://iraqithoughts.blogspot.com/2006/12/end-of-tryant.html

[8] http://www.blogger.com/terms.g

the period 1 May 2002 to 3 February 2011. For each post and comment, I extracted the title, author, content and publication and update date. I stored this data in a MySQL[9] database.

The posts were then preprocessed to detect the language used to enable comparison of Arabic versus English posts. I found that the actual language of the content was not always equal to that indicated in the metadata of the pages. While the language mentioned in the metadata of Figure 6 is British English, it is clear that the content of the corresponding post is instead written in Arabic.



A Family in Baghdad

mother: Faiza, sons: Raed, Khalid , an

ntributors
d Jarrar
a Al Arji
ed Jarrar
id jarrar

cted by MASTER BLOGS'
ide to Outstanding Blogs

Sunday

```
<iframe src="http://www.blogger.com/navbar.g?targetBlogID=616104
amp;blogName=A+Family+in+Baghdad&amp;publishMode=PUBLISH MODE BLC
amp;navbarType=BLACK&amp;layoutType=CLASSIC&amp;searchRoot=http%3
%2Fafamilyinbaghdad.blogspot.com%2Fsearch&amp;blogLocale=en GB&
amp;homepageUrl=http%3A%2F%2Fafamilyinbaghdad.blogspot.com%2F" ma
```

العراق المحتل ووجه اميركا القبيح ....

الاثنين 10 أيار 2010

السلام عليكم ,

كنت في زيارة لبغداد الحبيبه / الحزينه / الصابرة / التي تعيش تحت الاحتلال...
بيغداد رأيت معنى كلمة الاستعمار / رأيتها في الشوارع القذره المحفرة المهمله / رأيتها في البنايات القديمة التي تراكم عليها الغبار
والاهمال / رأيتها في صورولوحات تعبر عن الطائفيه في شوارع العراق / رأيت العراق بعيون اجدادي الذين عاشوا زمن الاحتلال
البريطاني / زمن التخلف والظلام والظلمات,

Figure 6: Contradiction Between the Declared and the Used Languages

This contradiction led to the design the algorithm described in Figure 7. A post that had more than 50% of the characters (after excluding email addresses and hyperlinks) as Arabic letters was classified as an Arabic post. Similarly, a post that had more than 50% of the characters (after excluding email addresses and hyperlinks) as Latin letters was classified as an English post. This algorithm was based on the assumption that posts having dominant Arabic characters are Arabic posts even if there are other languages that are written in Arabic characters such as Persian and Urdu. I assumed also that posts having dominant Latin characters are English posts, even if these characters can be used in other European languages.

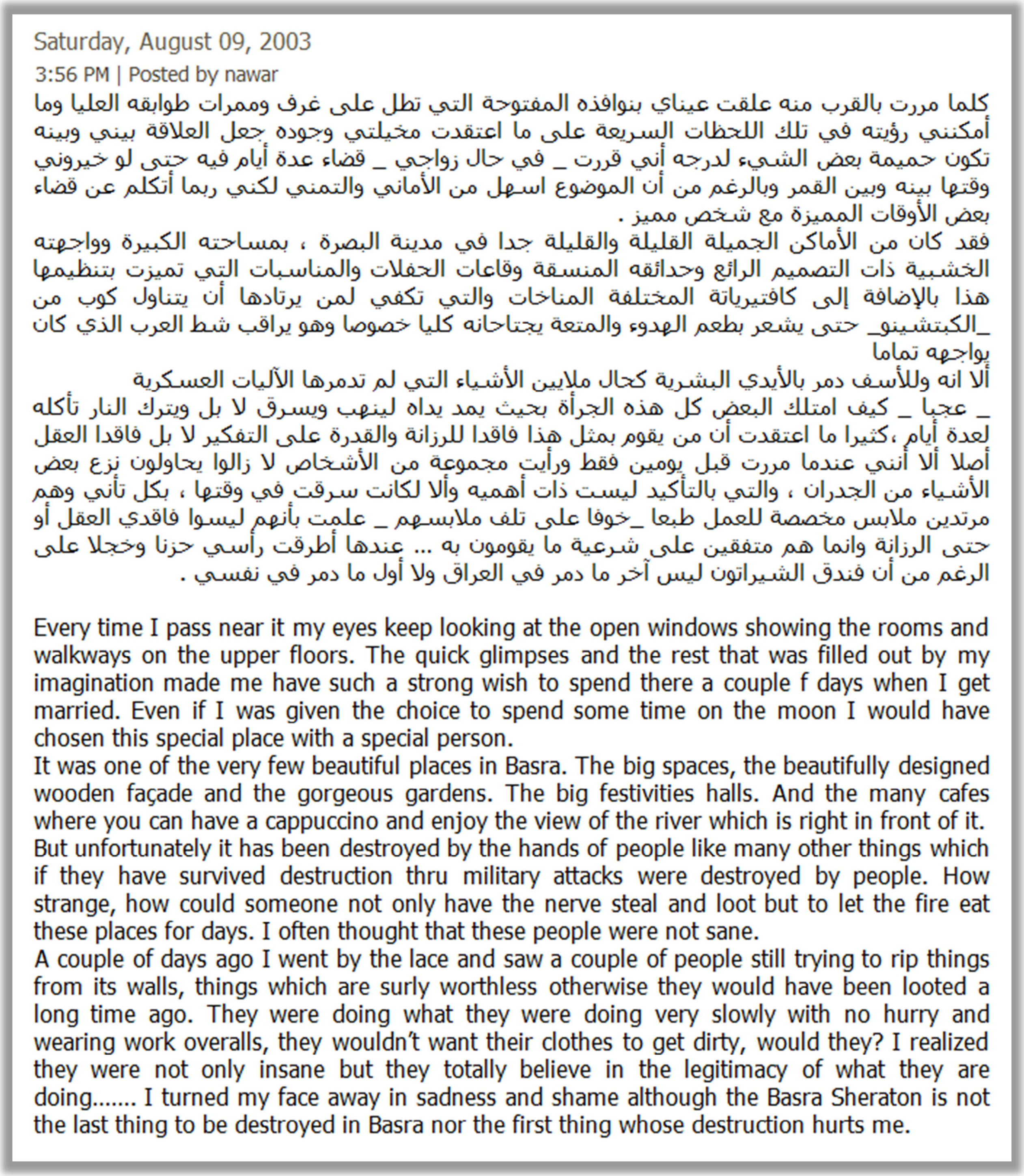
[9] http://www.mysql.com

```
Function getLanguage(post):
    • count(Arabic) ← 0
    • count(Latin) ← 0
    • count(Other) ← 0
    • Remove all URLs and email addresses.
    • For each character c in the post:
        o If c is an Arabic character, then count(Arabic) ← count(Arabic) + 1
        o Else if c is a Latin character, then count(Latin) ← count(Latin) + 1
        o Else (i.e. c is a space, punctuation, special character or a character from any
          other alphabet), then count(Other) ← count(Other) + 1
    • If count(Arabic) > count(Latin) + count(Other), then return "Arabic"
    • Else if count(Latin) > count(Arabic) + count(Other), then return "English"
    • Else return "Undetermined"
```

Figure 7: Language Detection Algorithm

This scheme returned 11,668 Arabic posts and 31,246 English posts. In the remaining undetermined 3,914 posts, the dominant characters were neither Arabic nor Latin, and were excluded them from the datasets.

In the example of Figure 8, the length of the post is 3087 characters. The count of Arabic characters is 1172 (i.e. 38% of the length of the post), and the count of English characters is 1304 (i.e. 42% of the length of the post). As none of these percentages exceeds 50%, the algorithm succeeded in excluding this post from the dataset.



Saturday, August 09, 2003

3:56 PM | Posted by nawar

كلما مررت بالقرب منه علقت عيناي بنوافذه المفتوحة التي تطل على غرف وممرات طوابقه العليا وما
أمكنني رؤيته في تلك اللحظات السريعة على ما اعتقدت مخيلتي وجوده جعل العلاقة بيني وبينه
تكون حميمة بعض الشيء لدرجه أني قررت _ في حال زواجي _ قضاء عدة أيام فيه حتى لو خيروني
وقتها بينه وبين القمر وبالرغم من أن الموضوع اسهل من الأماني والتمني لكني ربما أتكلم عن قضاء
بعض الأوقات المميزة مع شخص مميز .

فقد كان من الأماكن الجميلة القليلة والقليلة جدا في مدينة البصرة ، بمساحته الكبيرة وواجهته
الخشبية ذات التصميم الرائع وحدائقه المنسقة وقاعات الحفلات والمناسبات التي تميزت بتنظيمها
هذا بالإضافة إلى كافتيرياتة المختلفة المناخات والتي تكفي لمن يرتادها أن يتناول كوب من
الكبتشينو حتى يشعر بطعم الهدوء والمتعة يجتاحانه كليا خصوصا وهو يراقب شط العرب الذي كان
يواجهه تماما

ألا انه وللأسف دمر بالأيدي البشرية كحال ملايين الأشياء التي لم تدمرها الآليات العسكرية

_ عجبا _ كيف امتلك البعض كل هذه الجرأة بحيث يمد يداه لينهب ويسرق لا بل ويترك النار تأكله
لعدة أيام ،كثيرا ما اعتقدت أن من يقوم بمثل هذا فاقدا للرزانة والقدرة على التفكير لا بل فاقدا العقل
أصلا ألا أنني عندما مررت قبل يومين فقط ورأيت مجموعة من الأشخاص لا زالوا يحاولون نزع بعض
الأشياء من الجدران ، والتي بالتأكيد ليست ذات أهميه وألا لكانت سرقت في وقتها ، بكل تأني وهم
مرتدين ملابس مخصصة للعمل طبعا _خوفا على تلف ملابسهم _ علمت بأنهم ليسوا فاقدي العقل أو
حتى الرزانة وانما هم متفقين على شرعية ما يقومون به ... عندها أطرقت رأسي حزنا وخجلا على
الرغم من أن فندق الشيراتون ليس آخر ما دمر في العراق ولا أول ما دمر في نفسي .

Every time I pass near it my eyes keep looking at the open windows showing the rooms and walkways on the upper floors. The quick glimpses and the rest that was filled out by my imagination made me have such a strong wish to spend there a couple f days when I get married. Even if I was given the choice to spend some time on the moon I would have chosen this special place with a special person.

It was one of the very few beautiful places in Basra. The big spaces, the beautifully designed wooden façade and the gorgeous gardens. The big festivities halls. And the many cafes where you can have a cappuccino and enjoy the view of the river which is right in front of it.

But unfortunately it has been destroyed by the hands of people like many other things which if they have survived destruction thru military attacks were destroyed by people. How strange, how could someone not only have the nerve steal and loot but to let the fire eat these places for days. I often thought that these people were not sane.

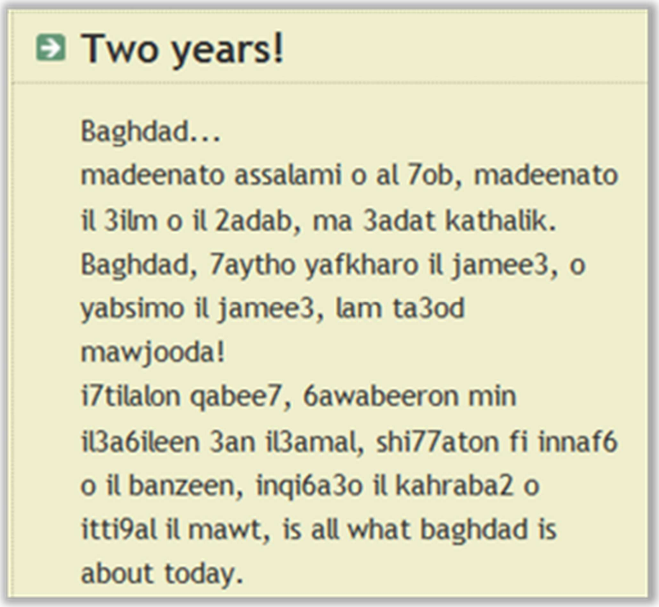
A couple of days ago I went by the lace and saw a couple of people still trying to rip things from its walls, things which are surly worthless otherwise they would have been looted a long time ago. They were doing what they were doing very slowly with no hurry and wearing work overalls, they wouldn't want their clothes to get dirty, would they? I realized they were not only insane but they totally believe in the legitimacy of what they are doing....... I turned my face away in sadness and shame although the Basra Sheraton is not the last thing to be destroyed in Basra nor the first thing whose destruction hurts me.

Figure 8: Arabic Content with its Translation in the Same Post[10]

[10] http://ishtartalking.blogspot.com

To verify the assumption, I manually coded a random sample of 1% of the posts that were classified as either Arabic or English posts. In all of the coded 117 Arabic posts, the dominant language was Arabic. For the coded 313 English posts, 311 of them were verified to be English. In the other 2 posts, one[11] was all about code written in Java, and the other[12] had only the word *dEsIGn70s*. This verification demonstrates the reliability of this algorithm (100% for Arabic and 99% for English), and thus make the character-to-language assumption justifiable.

One case I encountered that shows a limit of this algorithm is illustrated in Figure 9. In this post, the author chose to use Latin characters to write Arabic words. The algorithm classified it as an English post though one would like to have it returned as undetermined. However, I didn't see a similar case in the random sample. Thus, I assume that this represents a relatively rare case.



Two years!

Baghdad...
madeenato assalami o al 7ob, madeenato il 3ilm o il 2adab, ma 3adat kathalik.
Baghdad, 7aytho yafkharo il jamee3, o yabsimo il jamee3, lam ta3od mawjooda!
i7tilalon qabee7, 6awabeeron min il3a6ileen 3an il3amal, shi77aton fi innaf6 o il banzeen, inqi6a3o il kahraba2 o itti9al il mawt, is all what baghdad is about today.

Two years!

Baghdad…

The city of peace and love, the city of science and art, is no more what it was.

Baghdad, where everyone is proud, and everyone is smiling, doesn't exist anymore!

An ugly occupation, lines of unemployed, scarcity in oil and gas, power outage and death transmission, is all what baghdad is about today.

Figure 9: Arabic Text Written in Latin Characters,[13] with its Translation

[11] http://ukitech.blogspot.com/2008/07/hibernate-disjunction.html
[12] http://shlonkombakazay.blogspot.com/2005/02/design70s.html
[13] http://allahkareem.blogspot.com/2005/04/two-years.html

Figure 10 shows the evolution of publication activity in the crawled period for Arabic and English posts. Figure 11 presents the growth of active authors during the same period. An author is active in a month for a determined language if she has published at least one post in this month and language. Thus, an author might be active for both languages in the same month if she published 2 posts in 2 different languages, or might be inactive if she didn't have any publication in that month.

In both figures 12 and 13, I notice that English content shows a rapid increase, while the Arabic posts didn't emerge until the beginning of 2009.

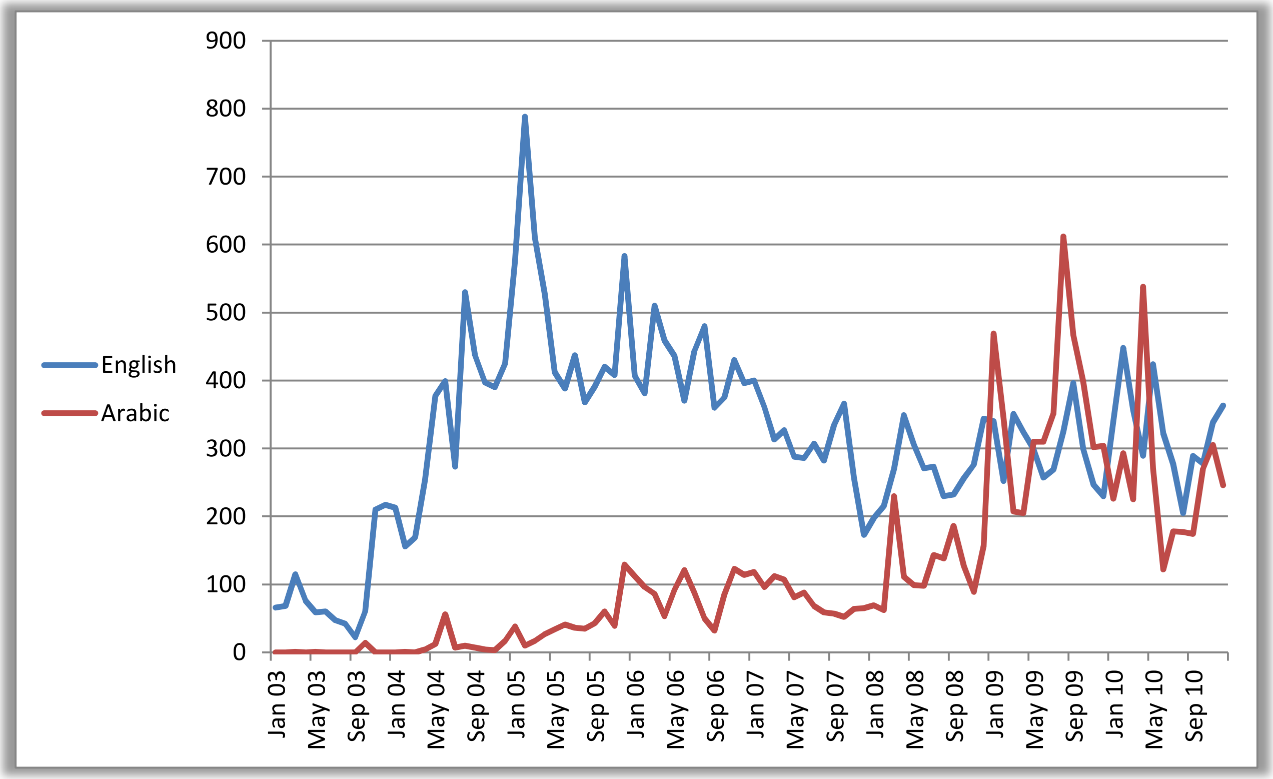


Figure 10: Number of Topics per Month

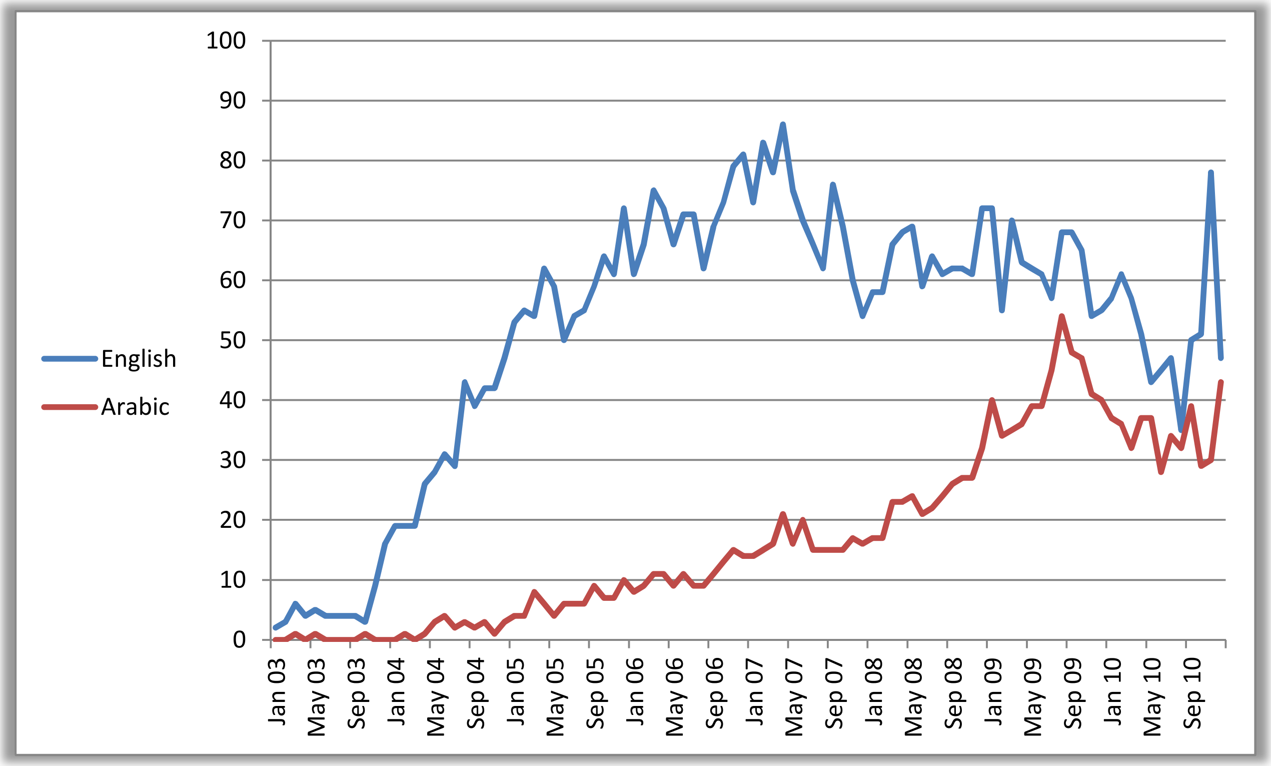


Figure 11: Number of Active Authors per Month

2.4. Preprocessing

2.4.1. Morphological Analysis

Posts were tokenized and stemmed. The Porter stemmer [16] and Buckwalter morphological analyzer [7] were used respectively for English and Arabic posts. My preliminary work showed that the use of stemming was of some benefit for English, and critical for Arabic. In fact, it minimizes the loss of shared meaning of different forms of the same root. Table 1 shows for instance that the lemma *countri* was retrieved for its different forms: *countries* and *country*. This computation was more interesting for Arabic because of the morphological complexity of the language, as words can have a large number of forms when they get concatenated to articles and prepositions.

2.4.2. Porter stemmer

Porter's stemmer is considered to be the most common English stemmer. Porter's algorithm is 5 sequential steps that consist of the selection and application of a rule from a set of rules. Because of space considerations, I limit the description of the whole algorithm to some illustrations of rules' usage:

Rule			Example		
SSES	**→**	**SS**	caresses	→	caress
IES	**→**	**I**	countries	→	countri
Y	**→**	**I**	country	→	countri
SS	**→**	**SS**	caress	→	caress
S	**→**		cats	→	cat

Table 1: Examples of Usage of Porter's Stemmer

2.4.3. Buckwalter morphological analyzer

Tim Buckwalter developed a morphological analyzer for the Arabic language. This analyzer is based on 3 lexicons: prefix, stem and suffix dictionaries. The parser tries to match the input to possible concatenation combinations and returns a list of possible fragments. Figure 12 shows the output provided by this morphological analyzer of an Arabic word. In this analysis, I kept only the first solution if many possibilities were returned.

Without stemming, words like "بلدي" (my country), "بلدك" (your country), and "بلدنا" (our country) would be considered by the algorithms presented in the next sections as independent terms even if linguistically the lemma "بلد" (country) is shared among them.

```
INPUT STRING: اليوم

LOOK-UP WORD: Alywm

  SOLUTION 1: (Aloyawoma) [yawom_3] Aloyawoma/ADV

     (GLOSS):  + today +

  SOLUTION 2: (Alyawom) [yawom_1] Al/DET+yawom/NOUN

     (GLOSS): the + day +

  SOLUTION 3: (Alyawom) [yawom_4] Al/DET+yawom/NOUN_PROP

     (GLOSS): the + Youm +
```

Figure 12: Example of Usage of Buckwalter's Morphological Analyzer

2.4.4. Indices properties

Table 2 summarizes the main properties of the indices. For each language, documents count is the count of posts. Vocabulary size is the count of unique words after stemming. Terms count is the count of all occurrences of all the words in the index.

	Arabic Index	English Index
Documents count	11,668	31,246
Vocabulary size	73,250	126,100
Terms count	4,783,395	5,934,079

Table 2: Indices Properties

In an imaginary dataset of 2 documents *one fish two fish*, and *red fish blue fish*, the vocabulary size would be 5, and the terms count would be 8.

Now that I have the data gathered and preprocessed, I can start the quantitative analysis. In next chapter I present my first attempts with classification and clustering.

Chapter 3 Initial Analysis Attempts: Classification and Clustering

This chapter presents 2 different approaches for the analysis of crawled posts. The former is a supervised technique (classification), and the latter is an unsupervised one (clustering). I discuss the limits of both techniques to the special case that the crawled data represemt.

3.1. Classification

Classification is a supervised machine learning group of methods that aim to assign documents to a predefined set of classes. Classes can be defined by rules provided by domain experts, or based on previously classified elements that can be used as a training data for the upcoming documents. The families of algorithms used most for text classification are Bayesian classification, vector space classification and support vector machines.

The only classification effort related to this research that I am aware of was performed by Al-Ani, Mark and Semaan [1]. The methodology as explained in this paper consisted of the analysis of the first 5 posts of a sample of 27 Iraqi blogs. Each blog was then assigned to one of the four categories *art*, *diary personal, diary war* and *journalism*. This classification approach has two main issues; first the classification concerns blogs instead of posts, which is supposing that all of the content of a blog is strictly about one unique category. Second, in my preliminary investigation of the posts, I found some topics, for instance about religion and electronics, which cannot fit in these four categories. I decided then to categorize the data with an unsupervised approach to see if I could infer more knowledge.

3.2. Clustering

3.2.1. Definition

Clustering is an unsupervised machine learning set of algorithms that group documents into clusters based on their similarity. Documents from the same cluster should be as similar as possible, while documents from different clusters should be as dissimilar as possible. Similarity can be computed by a distance metric in which similarity between two documents is inversely proportional to the distance that separates them.

3.2.2. K-Means

K-means is a popular clustering algorithm that aims to minimize the average Euclidian distance between documents of the same cluster and its center or *mean*. This algorithm starts by selecting ***K*** random documents as ***K*** centers for the future clusters. Each document in the dataset will be assigned to the cluster of the nearest center. At the end of this iteration, a new center is computed for each cluster. These steps can be repeated until convergence is achieved or a fixed number of iterations is reached. The final result is a subdivision of the dataset into ***K*** distinct clusters.

3.2.3. Implementation

I implemented the K-Means algorithm as described in Figure 13 on the English and Arabic posts separately. I based the implementation on Lucene[14]. I used the cosine similarity to compute the similarity ***sim (d, d')*** between two documents ***d*** and ***d'***.

```
1. Create $k$ empty clusters.
2. Select $k$ random posts from the dataset, and assign each as a centroid to a cluster.
3. While computation has not converged yet
    a. For each document in the dataset different than the centroids
        i. Compute the distance between this document and each centroid.
        ii. Assign the document to the cluster that minimizes this distance, i.e. The
            cluster that maximizes the similarity among its centroid in the document.
    b. For each cluster
        i. For each document $d$: $s(d) \leftarrow 0$
            • For each document $d'$ different than $d$: $s(d) \leftarrow s(d) + sim(d, d')$
        ii. Choose the document $d$ that maximizes $s(d)$ and set it as a new centroid.
4. Return $k$ clusters
```

Figure 13 - K-means Algorithm

3.2.4. Results

I ran my implementation first to retrieve 10 clusters. Table 3 presents the most frequent terms in each cluster. The reader can easily identify the dominant topics of many clusters. Cluster CE02 contains probably religious posts, as we find terms like *god*, *bible*, *spirit*, *jesus*,

[14] http://lucene.apache.org

faith. CE03 can be a cluster of French posts not excluded from the dataset with the language detection algorithm presented in section Figure 7. CE05 may be about online entertainment. However, 9 of the 10 clusters represent less than 8% of the number of English posts (Figure 14). All of the other 92% are clustered together in CE09. Unfortunately, it is difficult to infer one dominant topic in this cluster. One may instead retrieve a daily life topic (*time*, *people*, *work*, *call*, *friend*), a political topic (*government*, *american*) and a violence topic (*war*, *kill*).

ID	Cluster
CE01	upload origin nofril tokyo japanes photo ル flickr ビ の info html net seesaa blog articl ・ て 片 倉 japan い か り august ら と view read は
CE02	god day bibl spirit jesus road faith life post thing love morn time holi light live yesterday avila philippin talk motiv call peac better mel save peopl alarilla christ tag
CE03	de la en le les il se à dan est des qui une du pour au ce sur tout je comm ne par pas mai avec son san bien leur
CE04	pictur site ann post googl cat hey i'm time you'r nice coulter check search read well day link pic year cool laugh good trip click peopl top video hope photo
CE05	site news googl click internet web check onlin user start blog work provid busi compani armenian servic file develop websit imag market game video free network access find armenia creat
CE06	american soldier museum armenian nativ video news النحاتgenocid idol read muslim william barb street mosqu kid pride washington agress file jew movi sculptor recogn ot op wink turk heartless
CE07	japan tokyo upload nofril origin tower water の august 水 給 estat click 塔 jutaku asagaya view octob 阿 北 宅 地 に 住 あ 佐 residenci morn ケ imag
CE08	love time good life post day blog friend happi i'm peopl read thing best learn year feel live long help heart find true nice go well care lot better thought
CE09	time peopl iraq iraqi day year thing well good work call live countri al go start baghdad today govern post life read war american place long kill friend talk feel
CE10	hello post baghdad amman cairo pictur storey shop morn view today center commerci garden hous small beauti roman flower ladi wear museum good ceram yesterday room egyptian north mosqu piec

Table 3: Most Frequent Terms in a Partitioning of 10 English Clusters (CE = Cluster in English)

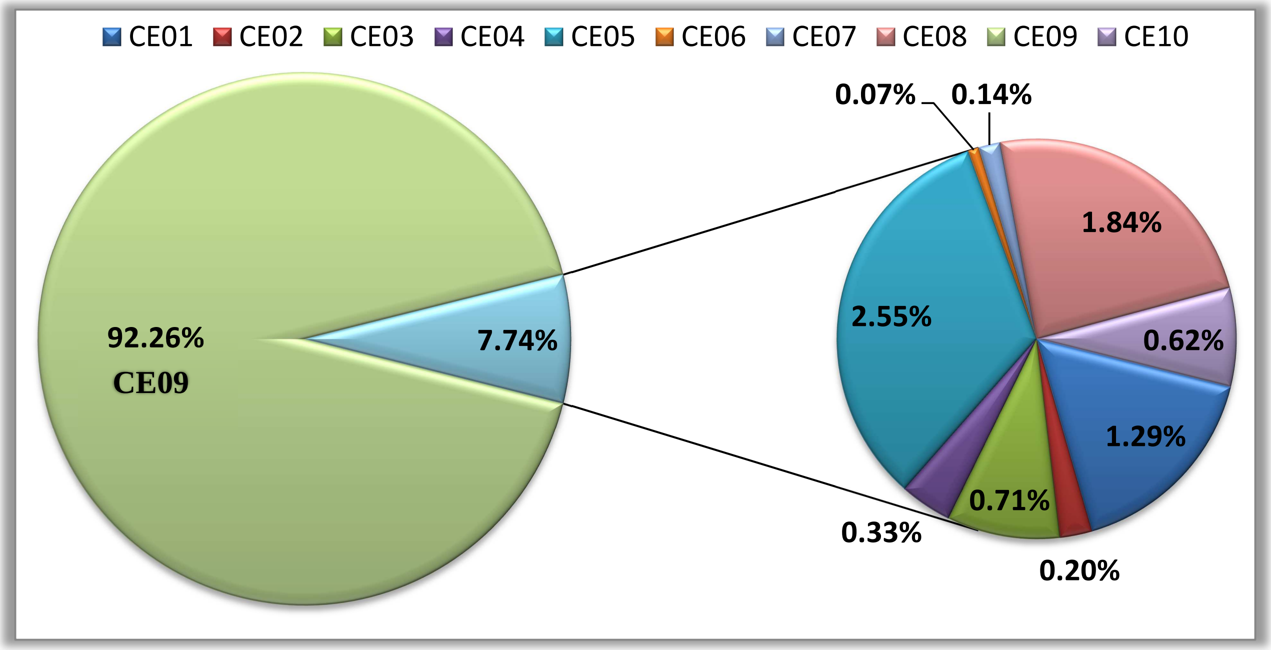


Figure 14: Distribution of Documents Over a Partitioning of 10 English Clusters

I then tried another value of ***k***. For ***k = 20***, I made the same observation (Table 4, Figure 15). There was one dominant topic (CE'17) with more than 88% of the posts. And the frequent terms are almost the same encountered in CE09, and thus one can't conclude what is the distribution of the topics covered in this cluster.

ID	Topic
CE'01	test sourc damascus t cat amman click receiv cute view ic mosqu comput snowboardbrill الرسام logitech kinder chicago lernspielzeug webcam larger streetscen desk flower amawi class fuck big laubsaug code
CE'02	blog post day time blogger iraqi read start baghdad link write iraq comment check today i'm good pictur arab year find interest thing hello hope site al updat friend email
CE'03	god day bibl spirit road faith life post thing love morn time jesus holi light live yesterday avila philippin talk motiv call peac better mel save peopl alarilla christ tag

CE'04	fayrouz hancock mark texa pictur enjoy visit love photo display day photograph time camera newseagl life food festiv garden usual place dalla beauti beaumont cover work i'm famili nice good
CE'05	de la en le les il se à dan est des qui une du pour au ce sur tout je comm ne par pas mai avec son san bien leur
CE'06	dead fish boat iraqi left fire govern port ingredi persian cultur sea investig equip georg lorna appear vartan relax bfcdb chocolati chocol languag serviceman french desir spot defens free milk
CE'07	pictur ann site googl i'm hey search you'r cat well coulter time read check trip click pic nice year laugh peopl post video go doctor hope alright celebr cool news
CE'08	translat note ra html common librari post apach bit valid april help file consid mix gwt javascript review write site code size input hope て の ４ い inconveni し
CE'09	site googl click internet web user onlin work compani check busi provid servic develop start imag market game file websit video access free network find time good open set includ
CE'10	news armenian armenia asbarez turkey panorama visit turkish azerbaijan msnbc break economi hyemedia polit presid facebook hot aysor net panarmenian aliyev time azerbaijani link wikileak church expert attack hold good
CE'11	al link allah prophet jesus محمد ha moham islam symbol creat hay el plural testament text ادريس الحي entir elloah alqiayama القيامة code var azim vav creator chapter אל lam
CE'12	photo read origin build upload nofril flickr japanes articl net html blog seesaa ル ビ tokyo 京 の 目 り septemb hurri pictur info demolish ・ 大 offic 片 倉
CE'13	japan upload tokyo nofril origin tower water の august 水 給 estat click 塔 jutaku asagaya view octob 阿 北 宅 地 に 住 あ 佐 residenci morn ヶ imag
CE'14	upload origin nofril tokyo august japan view wall march cherri tv close larg roppongi photo ル mark screen tuma pictur day の paint nagai 暁 dawn report wiki kenji yellow
CE'15	waghorn eduardo learn chile copyright nada hace la escribir friend para hug por te comienzo industri dolor pleno medley seguiré medio se tren año doquier record una memoria sentir hay

CE'16	hello post amman baghdad cairo shop morn view hous garden small today beauti roman ladi wear flower museum ceram good yesterday egyptian piec build downtown kitten ruin insid apart plant
CE'17	time peopl iraq iraqi day year thing well good work call live countri al go start baghdad govern today life war read american post kill place long friend talk feel
CE'18	armenian genocid news armenia call recogn mp asbarez resolut turkey net panarmenian turkish eu court karabakh azerbaijan european hous pelosi polit vote download panorama recognit time anca res azerbaijani hyemedia
CE'19	net panarmenian japanes upload 片 倉 nofril seesaa articl html info ル ・ ビ blog origin の か て に い り ら ŀ ロ ま た す っ は
CE'20	upload nofril origin photo blue descript english japanes short flickr info box て い が の る 内 所 都 某 は に う か し た り れ も

Table 4: Most Frequent Terms in a Partitioning of 20 English Clusters

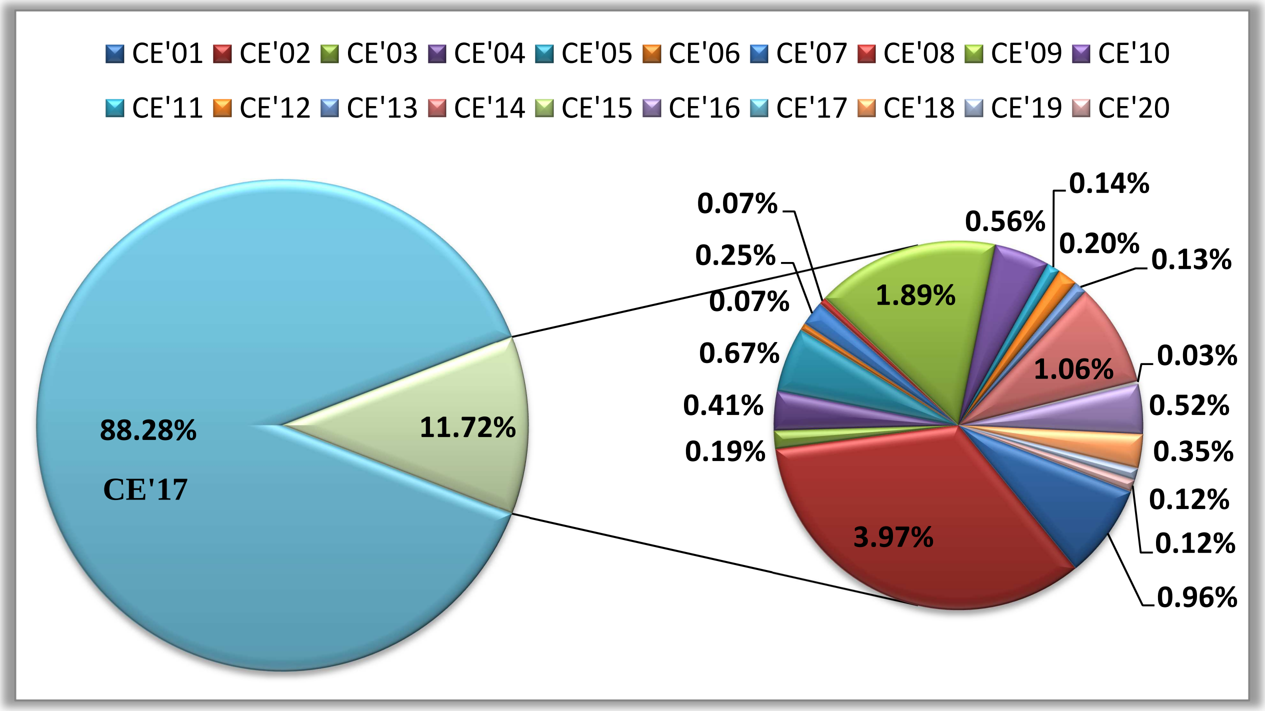


Figure 15: Distribution of Documents Over a Partitioning of 20 English Clusters

I argue that these results are due to the size of the posts (few paragraphs), which allows bloggers, unlike in micro-blogging platforms like Twitter, to cover multiple topics in a single post. This led me to try another alternative: topic modeling.

Chapter 4 Topic Modeling

After experiencing the limits of classification and clustering in the previous chapter, I investigate, in this one, another unsupervised technique: topic modeling. Once I define this technique, I discuss some of the related work in the literature. I next present my implementation and show my findings.

4.1. Definition

Topic models are probabilistic models for discovering latent topics of a set of documents. The idea behind these models is that words presented in a document are generated from a hidden process based on their association to some topics. In other terms, words like *cats* and *dogs* are more likely to appear together in a document rather than showing up with *stock market*. Thus, the process tries to find the mixture of topics that generated the documents in the corpus, while a topic itself is a probability distribution of correlated words over the vocabulary [5]. Latent

Dirichlet Allocation (LDA) is the most common use of topic models. The LDA model assumes the following generative process for each document $\boldsymbol{d}$ in a corpus $\boldsymbol{D}$:

1. Choose the topic distribution $\boldsymbol{\theta_d}$ from a uniform Dirichlet prior with parameter $\boldsymbol{\alpha}$.

   $\boldsymbol{\theta_d} \sim \mathrm{Dir}(\boldsymbol{\alpha})$

2. For each word $\boldsymbol{w_d}$ in the document $\boldsymbol{d}$:

   a. Choose a topic $\boldsymbol{z_{w,d}}$ from a multinomial distribution with parameter $\boldsymbol{\theta_d}$.

      $\boldsymbol{z_{w,d}} \sim \mathrm{Multinomial}(\boldsymbol{\theta_d})$

   b. Choose a word $\mathbf{w_d}$ from a multinomial probability with parameter $\boldsymbol{\beta}$ conditioned on the topic $\boldsymbol{z_{w,d}}$.

      $\mathbf{w_d} \sim \mathrm{Multinomial}(\boldsymbol{\beta_{Zw,d}})$

4.2. Related Work

Since the introduction of LDA in 2003, it has been applied to a wide variety of domains and applications, many of which include correlations with, and in some cases predictions of, events external to the model.[15] Yano, Cohen and Smith applied two variants of LDA to predict response to political blogs [19]. The first, LinkLDA, models the users most likely to react to a post. The second, CommentLDA, guesses the content of these comments.

Ramage, Dumais and Liebling tried to take the study of microblogging services "beyond their traditional roles as social networks" by implementing a Labeled LDA to translate the content of tweets into multidimensional characteristics [17]. This partially unsupervised learning

[15] Parts of this section were taken from [3].

model categorizes the learned dimensions into four categories: substance (events and ideas), social communication, status (personal updates) and language style.

Polylingual Topic Models were introduced by Mimno et al. to discover parallel topics across multilingual corpora that are either official translations (EuroParl) or corresponding articles from different languages (Wikipedia) [14]. These models were also used to compute the divergence between pairs of documents and infer the score of disagreement between languages.

Topic models were also presented as an approach to track the drift of topics over time in research fields by Hall, Jurafsky and Manning [10] as well as in weblogs related to "Toyota" and "iPhone" by Knights, Mozer and Nicolov [13]. In a preliminary examination, Kireyev, Palen and Anderson applied topic models to crisis-related microblog posts [12].

Some work was done to validate the analysis of social media from external facts. Bollen, Mao and Zeng investigated the correlation between the Dow Jones Industrial Average and Twitter feeds to find a causality relation between mood dimensions and stock market trends [6].

4.3. Implementation

I applied the Matlab Topic Modeling Toolbox [9] to the crawled collection. This toolbox needs 2 files as input. One (Table 5a) is a list of the unique words in the index. For each language, the size of this list corresponds to the vocabulary size presented in Table 2. The other (Table 5b) is a file containing the assignment of each word to its document. That is, in each line there are the ID of the document, the ID of the word and the number of occurrences of this word in that document. Thus, if a word ***w*** doesn’t exist in a document ***d***, there is no entry in the file for the tuple (***w***, ***d***). If this word was mentioned ***n*** times in that document, the file should have a corresponding entry of 3 values: ***w***, ***d*** and ***n***.

Line number	Word
1	a
…	…
47757	**iraq**
…	…
105524	war
…	…

Document ID	Word ID	Frequency
…	…	…
2	47757	4
5	47757	1
6	47757	1
13	47757	2
…	…	…

Table 5 (a, b): Structure of Input Files for MATLAB Toolbox

The toolbox uses Gibbs sampling to discover topics. The Gibbs sampler is a Markov chain Monte Carlo algorithm that can be used to infer the distribution that generated a set of observations. In the case of LDA, the observations are the documents with their words, and the distribution is the mixture of topics. This iterative algorithm starts by a random assignment of the values, which means that, at the beginning, each term gets a random topic. Then Gibbs is run over a fixed number of iterations or until convergence is reached. During each iteration, all of the terms are picked one by one randomly, and a topic is sampled based on the topic assignment of the previous terms of the same iteration. The reader should see [11] for more detailed explanation of the use of Gibbs sampler for the approximate inference of LDA.

This computation results in a matrix (M_1) that contains the assignment of each term to a topic. For the Iraqi crawled posts, this means that each of the 5,934,079 (4,783,395) terms in the English (Arabic) dataset has an assigned topic. This matrix is then used to generate two others. The first (M_2, Table 6) contains how many times a word of the vocabulary was assigned to each topic. The sum of each line is, thus, the count of times that word appears in the dataset. The second (M_3, Table 7) encloses the count of times the terms of a document were assigned to each topic. The sum of each line is, hence, the word counts of the corresponding document.

Topic ID Word ID	Topic 1	Topic 2	…	Topic T
…	…	…	…	…
47757	1	38895	…	190
47758	9	0	…	13
…	…	…	…	

Table 6: Matrix of Word/Topic Distribution

Topic ID Document ID	Topic 1	Topic 2	…	Topic T
…	…	…	…	…
13	12	1	…	8
14	9	0	…	13
…	…	…	…	

Table 7: Matrix of Document/Topic Distribution

M_2 was then used to get an order list of the most relevant words to each topic. In Table 6, the word of ID 47758 is more relevant to Topic 1 than the word of ID 47757.

I used M_3 to get the distribution of topics for each document as a percentage after normalizing the counts.

As the toolbox's developers suggest, I set the hyper-parameters Alpha and Beta to 50/T and 200/V where T is the number of topics and V is the size of the vocabulary. I ran 100 iterations. I tried various values of T. Table 8 shows the most frequent terms for the English posts in a portioning of 20 topics. I argue that the data set was "over-partitioned" in this case. In fact, I found many topics sharing the same meaning based on the most frequent terms. For instance topics TE'02 and TE'04 both have terms related to international politics: *Lebanon*, *Israel*, *Arab*, *Iran*, *Middle*, *East*, *America* and *Turkey*. TE'07 and TE'13 talk about daily life and share the words *life*, *time* and *talk*. The reader can also find similarities between topics TE'09 and TE'14, and between topics TE'10 and TE'19. In addition, I couldn't make sense of the correlation, in topic TE'01, between music terms (*song* and *Fayrouz*[16]), French words (*de*, *la*, *en*, *le*, *il* and *les*) and Arabic words (في and من).

ID	Topic
TE'01	de la hubbi Google en el le song file في من Fayrouz il Hancock les
TE'02	report prison Lebanon offic israel intern torture human court year author right release investigate charge
TE'03	book university year work play music team art student film school great study city
TE'04	Arab Iran Country Middle politic Iranian Israel east power support region regime nation America Turkey
TE'05	Iraqi election govern party Iraq vote politic Kurdish Kurd minister nation member constitution Maliki Kurdistan
TE'06	hand eye head man face turn left black stand walk street open door light move
TE'07	love time day feel I'm guy life remember happy ask smile call talk dream listen
TE'08	oil time year model t rate figure product nature number system term field discovery
TE'09	kill baghdad police bomb attack soldier Iraqi force wound army report military city
TE'10	news picture video tv site photo media busy Internet report image journalist watch
TE'11	muslim women God Islam Arab christian religion men man woman Allah live peace people life
TE'12	fact point case question matter discuss issue view interest public social person object reason article
TE'13	thing people good time go well I'm bad better life lot person talk thought change
TE'14	Iraqi people Iraq country Saddam live kill American war happen govern year help life
TE'15	receive radio turn high circuit connect control power signal design low set work

[16] Fayrouz is the name of a famous Arab singer.

TE’16	Iraq war American Bush Iraqi govern force president military unit administration troop plan year security
TE’17	water money company tea food price market electricity work pay car buy Obama
TE’18	t day house time family friend don told year car school Baghdad start work mother
TE’19	post read blog write time comment story friend blogger hope day start link email year
TE’20	Al Sunni Iraq Iraqi Baghdad Shiit Sadr Shia group city Qaeda Ali Islam armi Abu

Table 8: Most Frequent Terms in the English Posts in a Partitioning of 20 Topics (TE = Topic in English)

On the opposite side, Table 9 shows that using only 5 topics caused the merging of separable themes. For example, Topic TE’’03 could be separated into 2 different topics, one for local politics (*Iraqi*, *Iraq*, *politic*, *Saddam* and *govern*), and the other for international politics (*Arab*, *politic*, *muslim* and *American*). Similarly, topic TE’’04 could be split into 3 topics: economy (*oil* and *work*), local politics (*vote*, *election* and *Kurdish*) and electronics (*high*, *receive*, *power* and *turn*).

ID	Topic
TE’’01	post blog read book write picture de news site play year blogger music tea Internet
TE’’02	day time t thing people friend life feel live love start good I'm year family
TE’’03	Iraqi people Iraq Arab country Al Islam politic Saddam Muslim govern war American women live
TE’’04	time oil work vote election high number point Kurdish list well year receive power turn
TE’’05	Iraq Iraqi kill Baghdad Al war force American report govern attack security military bomb Bush

Table 9: Most Frequent Terms in the English Posts in a Partitioning of 5 Topics

I decided at the end to work with $\boldsymbol{T}$ = 10 topics. This doesn’t necessary imply that this is the perfect choice, but I believe it is a good one, specially that it was validated by human analysis. I used the same number of topics for both datasets (Arabic and English).

An alternative was provided by Griffiths and Steyvers to select T [9]. They proposed to estimate the likelihood $P(w|T)$ for different values of T. This likelihood, as a function of T, increases until reaching a maximum T_0, and then decreases. They suggest that this T_0 is the optimum number of topics.

4.4. Results

The ten topics discovered by the English and Arabic models are presented in Tables 5 and 6, respectively. The topics are presented in descending order of frequency, and each topic is illustrated with the words most relevant to the topic.

ID	Topic
TE01	People Iraqi Iraq Country American war Saddam live year kill America happen terrorist government
TE02	year work company busy develop tea market project system service money provide case program
TE03	day time t friend thing I'm feel start house talk go work good told car
TE04	Iraq Baghdad kill Iraqi force war attack military police bomb report American soldier bush army
TE05	Iraq al Iraqi govern politic elect Sunni party Iran Arab nation vote leader minister Kurdish
TE06	god women Muslim love life man Islam men heart person religion woman Christian face eye
TE07	oil de time receive model turn high t power radio la circuit set work point
TE08	al news year day today call Baghdad ago Abu watch TV video family play story
TE09	water picture city place black build white small food long game green open red photo
TE10	post read blog write Arab book comment university time blogger music link interest student publish

Table 10: Most Frequent Terms in the English Posts by Topic

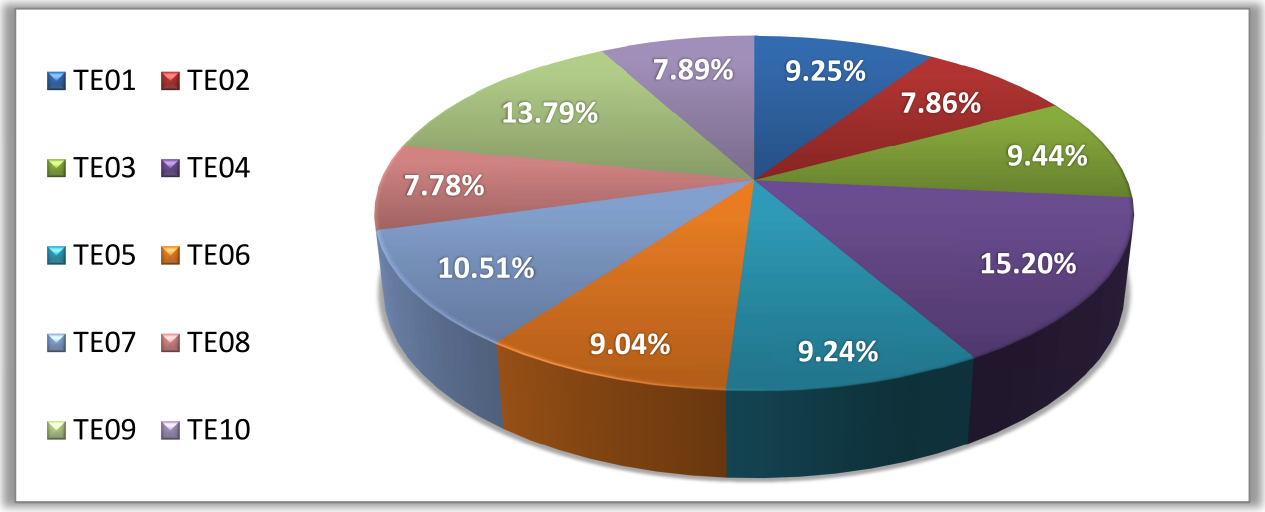


Figure 16: Distribution of English Topics

ID	Topic
TA01	احد يريد مر ايام نفس ذهب ناس يوم رجل قول سمع عرف قل كنت
	one want elapse days same go people day man saying listen know say was
TA02	حياة مرات شعر حب انس عين قلب موت ليل فن نفس جميل روح وجه صوت
	life times poetry love amiability eye heart death night art soul beautiful spirit face sound
TA03	الله ابن قال سلام ال امام صلى اسلام محمد قول اهل اب عبد مسلم رسول
	Allah son say peace the Imam pray Islam Mohammed saying kin father worshipper Muslim prophet
TA04	عراق ال قوات حكومة رئيس قال مجلس امن محافظة عملية بغداد زار امريكا انتخاب المالكي
	Iraq the force government president say council security governorate operation Baghdad visit America elections Al-Maliki
TA05	اخر كثير كتاب مكن كتب مدة شيء شخص نفس احد فعل صورة وقت موقع اكثر
	other many book enable write period something person same one do picture time site more

TA06	ال عالم دين تاريخ اخر عرب قول علم فكرة اول اصل ثقافة ارض ملك نفس
	the scholar religion history other Arab saying knowledge idea first origin culture earth own soul
TA07	عراق امريكا عرب شعب احتلال صدام حزب حرب بعث ايران وطن قوة اسرائيل مقاوم
	Iraq America Arab people occupation Saddam party war Ba'ath Iran nation force Israel resistant
TA08	ال بغداد احد مد يوم منطق ساعة اطفال سم عشر ثلاث كبير قتل سيارة
	the Baghdad one expand day logic hour children poison ten three big kill car
TA09	دول سياسة عمل متحد حال لا ال حكوم قوة اجتماع عام مجتمع جديد اخر حقوق
	country politic operation united state no the government force meeting general society new other rights
TA10	عمل عام اعلام شركة معلومة مكتب دراسة شبكة جامعة خدمة برنامج صحف مدير نظام برامج
	work year media company information office studying network university service program newspapers director system programs

Table 11: Translations of the Most Frequent Terms in the Arabic Posts by Topic (TA = Topic in Arabic)

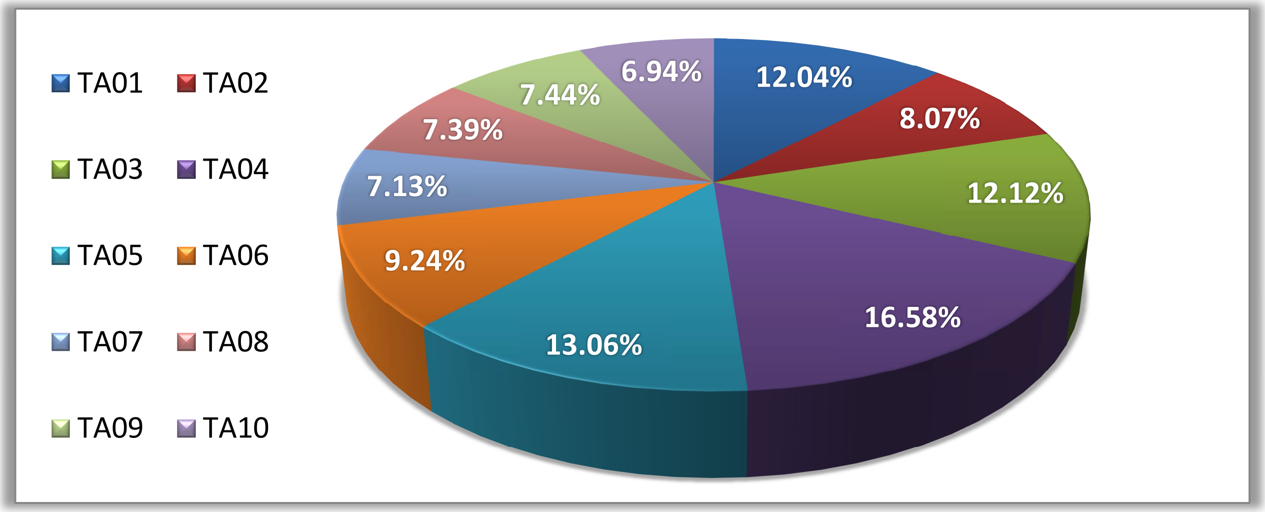
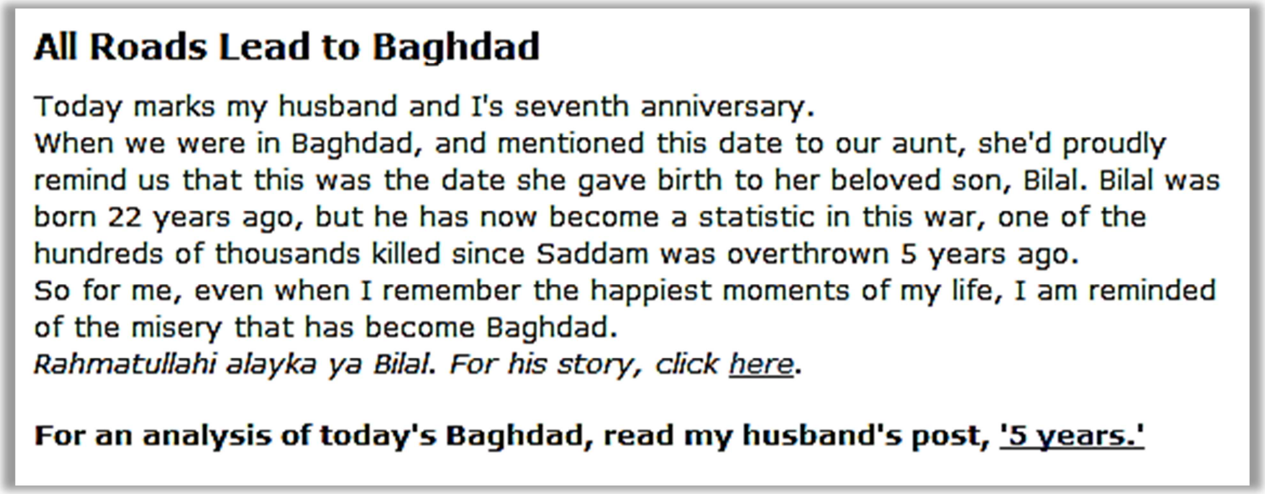


Figure 17: Distribution of Arabic Topics

To give an example, a single post (Figure 18) was analyzed and produced the distribution of topics present in this post (Figure 19), along with topic assignment to each token (Table 12).



All Roads Lead to Baghdad

Today marks my husband and I's seventh anniversary.
When we were in Baghdad, and mentioned this date to our aunt, she'd proudly remind us that this was the date she gave birth to her beloved son, Bilal. Bilal was born 22 years ago, but he has now become a statistic in this war, one of the hundreds of thousands killed since Saddam was overthrown 5 years ago.
So for me, even when I remember the happiest moments of my life, I am reminded of the misery that has become Baghdad.
Rahmatullahi alayka ya Bilal. For his story, click here.

For an analysis of today's Baghdad, read my husband's post, '5 years.'

Figure 18: Example of a Post[17]

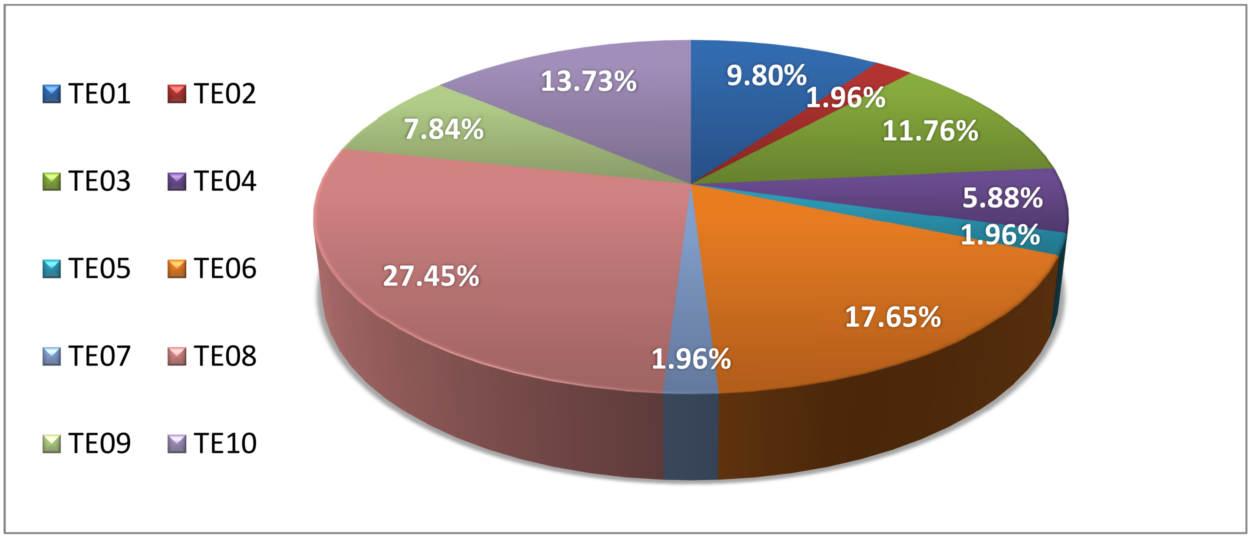


Figure 19: Distribution of Topics for the Post in Figure 18

[17] http://thoughtsfrombaghdad.blogspot.com/2008/03/all-roads-lead-to-baghdad.html

Topic	Terms
TE01	hundreds remind Saddam thousands war
TE02	statistic
TE03	aunt moments remember she'd story years
TE04	Baghdad killed roads
TE05	overthrown
TE06	alayka beloved birth husband husband lead life misery Rahmatullahi
TE07	analysis
TE08	ago ago anniversary Baghdad Baghdad Baghdad born mentioned seventh son today today ya years
TE09	happiest marks proudly years
TE10	Bilal Bilal Bilal click post read reminded

Table 12: Distribution of Tokens over Topics for the Post in Figure 18

I presented in this chapter the topics discovered in Arabic and English datasets. The next chapter will be dedicated to evaluating these results against an external source.

Chapter 5 Evaluation

The results of any unsupervised technique become more interesting if they can be evaluated against known facts from an external resource. In this chapter I demonstrate the success of the use of topic models by showing the high correlation of the timeline of war related topics with the Iraqi Body Count website.

In order to evaluate the output of the topic models, I looked for an external measure that captures the ongoing events during the war. Iraq Body Count[18] (IBC) is an independent nonprofit organization that made public its database of the "deaths caused by US-led coalition forces and paramilitary or criminal attacks by others" since 2003. Unlike other sources that provide estimates, IBC numbers are based on recorded and documented violent deaths from various sources such as journalists, hospitals, morgues, NGOs, and official statistics. Figure 20 illustrates

[18] http://www.iraqbodycount.org

the timeline of the body count for a period of 8 years as retrieved from IBC on February 16, 2011. The website notes that: “IBC’s figures are constantly updated and revised as new data comes in, and frequent consultation is advised.”

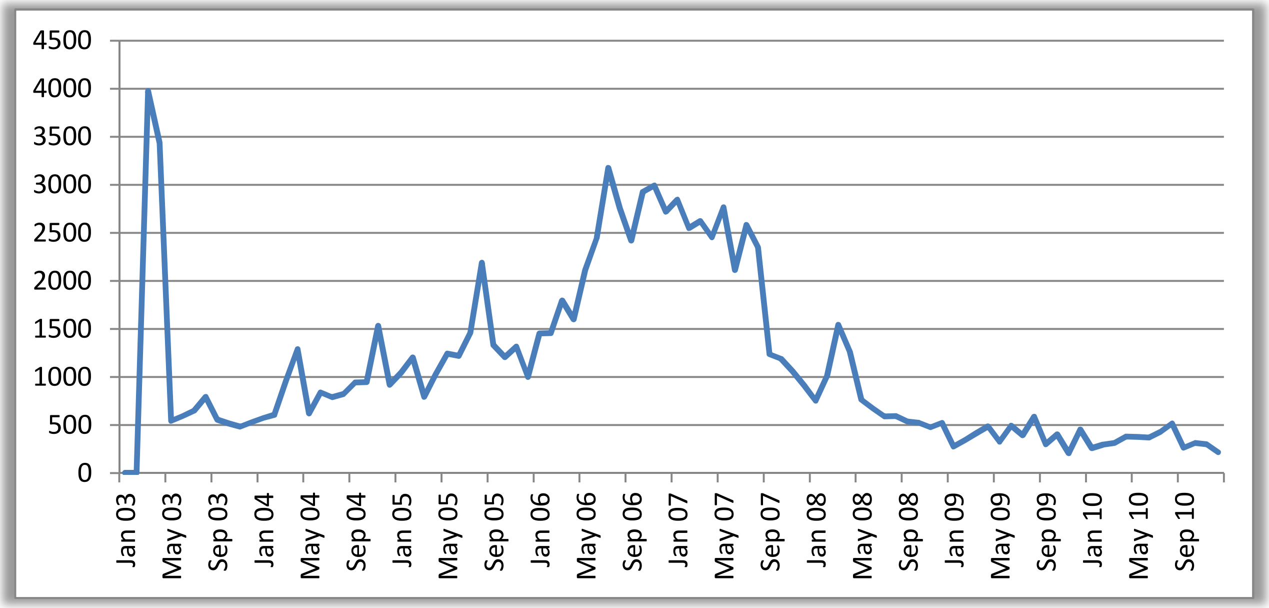


Figure 20: Body Count

The main topics that can be related to the body count are the ones that have more weight for war and violence terms. In TE01 and TE04 the reader can see, among the most frequent terms, the words *war*, *kill*, *terrorist*, *attack*, *military*, *bomb*, *report*, *soldier* and *army*. I merged these topics in the timeline presented by Figure 21. Similarly, I considered TA07 and TA08 as war topics for Arabic posts because of the appearance of the terms *occupation*, *war*, *force*, *resistant*, *poison* and *kill*. Their timeline is presented in Figure 22.

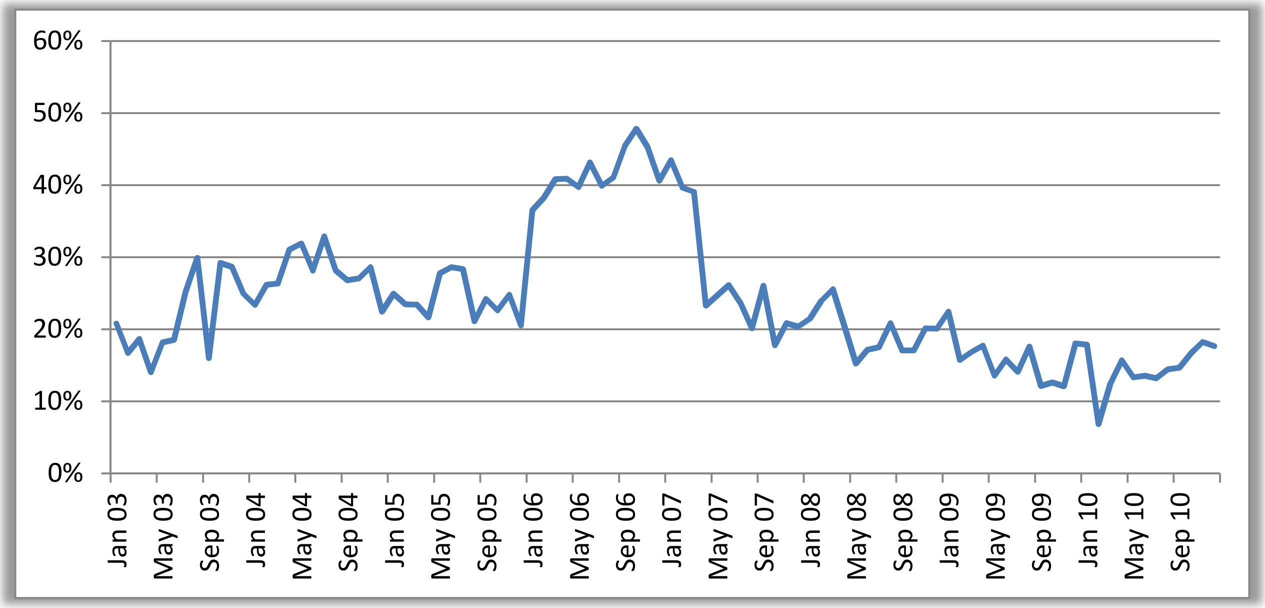


Figure 21: Timeline of War Topics in English

I found a highly significant positive correlation between the war topics and the body count. Lagging the body count after the war topics in English by two months I got a correlation coefficient ***R* = *0.8551*** and a level of significance ***p* < *0.001*** for a number of pairs ***N* = *84***. I limited the computation to the period 2004 – 2010, as in 2003 only a few posts were published (Figure 10). The high attention to violence themes by the bloggers in 2006 could be expected during a catastrophic condition described by the UN as “a civil war-like situation” [18]. This said, I can’t explain why the blogs were predicting the body count. I hypothized that bloggers were updating their posts after external events occurred, and I used posts’ update-date instead of publication-date. I got a very similar correlation coefficient (***R* = *0.8591***) for the same advance of two months. Further research is needed to clarify this behavior of relationship.

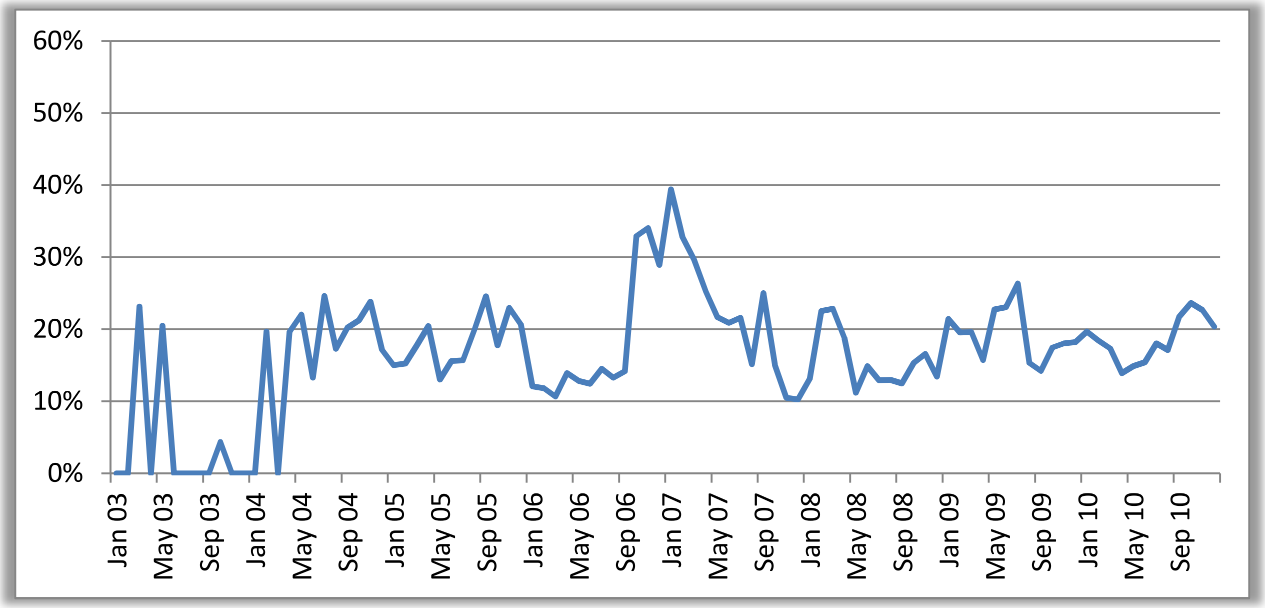


Figure 22: Timeline of War Topics in Arabic

The correlation of war topics in Arabic was less significant. This could be expected given that the blogging activity in Arabic didn’t emerge until 2009 (Figure 10). I claim that English posts are most likely to be generated by Iraqi bloggers living outside Iraq, and thus they don't face the lack of Internet accessibility that Arabic bloggers faced.

The high correlation of discovered topics with the body count confirmed the validity of the choice of topic models as a method for analyzing the big dataset of the blogs that I crawled. In the next chapter I review the problematic of the thesis and conclude with future work.

Chapter 6 Conclusion and Future Work

This thesis presented a method for the analysis of overabundant social data related to political crises. I showed series of steps and decisions that I took over the conduct of this project. I first introduced a Blogger-based crawler. I then proposed an algorithm for distinguishing Arabic and English posts in two independent datasets. In a preprocessing phase, I chose to integrate a morphological analyzer into each of them. Next I discussed the limitation of classification and demonstrated the inadequacy of clustering as a technique for investigating this specific data. Afterward I presented an implementation of topic models and showed its efficiency by finding a high correlation between the topics discovered and an external measure (the Iraqi body count). Overall, topic modeling can provide a rapid insight into a big dataset that we don't have any a priori knowledge about. The alternative of manually analyzing the data is challenging because finding a random representative sample may not be possible if the number of documents exceeds several thousands.

Some improvement to this effort can be done in future work. In any particular dataset that is similar to the one presented in this thesis, in which there is a prior knowledge of the dominant languages coming from different alphabets, the algorithm presented in Figure 7 can be adapted such that the number of possible outputs will be equal to the number of distinct alphabets. Nevertheless, this algorithm will fail in a mixture of documents, for instance, from various European languages. As section 3.2.4 shows, clustering returned a group of documents in which the most frequent terms are French words. Clustering can be used, then, for language detection instead of a character-count-based algorithm. A machine translation service can also be used to avoid eliminating content that is available in languages that a researcher doesn't understand.

In addition, I plan to verify if the same adopted approach and choices will work for other datasets. I think of using this work toward the analysis of data being collected these days about the political changes in the Middle East, as part of the efforts being made in the EPIC project. One challenge could be the adaptation of the algorithms to microblogging based data, known for the challenges presented by length limits, versus the relatively long posts that I have collected from Iraqi blogs.

The analysis of the comments can enrich this work. They can be used to get a better understanding of the interaction between the bloggers or between authors and their followers. In a preliminary trial, I found that topic models can be used for spam detection on the comments. In a run of 10 topics, I got two clear spam topics: pornography and gambling. After eliminating the comments that have most contribution to these topics, I may get cleaner data. I can also use comments for running topic modeling on all of the data instead of having two separate runs (one for English and another Arabic). I want to verify if comments help to correlate Arabic and English posts. In fact, comments are not necessarily published with the same language of their posts, and thus topic modeling might discover correlated words from different languages.

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